

Lecture 4: Stationary Distributions

Last
Time

Transition matrix: P

Initial data: $\vec{\mu} = (\mu_1, \dots, \mu_{|X|})$, where

$$\mu_j = \mathbb{P}(X_0 = i_j), \quad \mathbb{P}(X_1 = i_k) = (\vec{\mu}P)_k, \quad \text{and}$$

$$\mathbb{P}(X_n = i_k) = (\vec{\mu} \cdot P^n)_k$$

$$\text{Suppose } \mathbb{P}(X_0 = x) = \begin{cases} 1 & \text{if } x = i_k; \\ 0 & \text{else.} \end{cases}$$

Then the initial data $\vec{\mu} = (0, \dots, 0, 1, 0, \dots, 0) = \delta_{i_k}$.
"k-th" entry

"Dirac mass @ i_k ".

Today

1^o Q: Suppose the chain starts at i_k , i.e., $\vec{\mu} = \delta_{i_k}$,

What is the long time behaviour?

Let $\vec{\mu}^{(n)}$ be the distribution of X_n , i.e.,

$$[\vec{\mu}^{(n)}]_j = \mathbb{P}(X_n = i_j). \text{ Then what is}$$

$$\lim_{n \rightarrow \infty} \vec{\mu}^{(n)} = ?$$

Ex1. (2 coffee shops)

Suppose there are two coffee shops: Tim Hortons and Starbucks. The following Markov chain describes the probability of going to each coffee shop given which coffee shop is visited last time.

$$P = \begin{array}{c} \\ \begin{array}{cc} T & S \\ \begin{array}{c} T \\ S \end{array} & \begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix} \end{array} \end{array}$$

Q: What is the long time behaviour?

$$A: [\vec{\mu}(n)]_T = [\vec{\mu} P^n]_T = \vec{\mu}_T [P^n]_{TT} + \vec{\mu}_S [P^n]_{ST},$$

From the left figures, we know

$$\lim_{n \rightarrow \infty} [P^n]_{TT} = \lim_{n \rightarrow \infty} [P^n]_{ST} = 0.75,$$

$$\text{and } \lim_{n \rightarrow \infty} [P^n]_{SS} = \lim_{n \rightarrow \infty} [P^n]_{TS} = 0.25.$$

$$\text{Thus, } \lim_{n \rightarrow \infty} [\vec{\mu}(n)]_T = 0.75 (\vec{\mu}_T + \vec{\mu}_S) = 0.75,$$

$$\text{and } \lim_{n \rightarrow \infty} [\vec{\mu}(n)]_S = \lim_{n \rightarrow \infty} (1 - [\vec{\mu}(n)]_T) = 0.25.$$

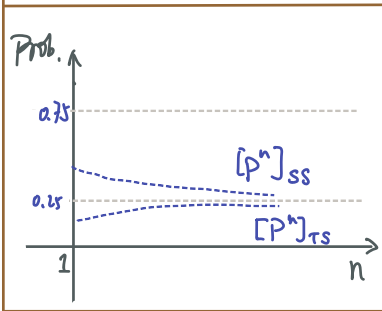
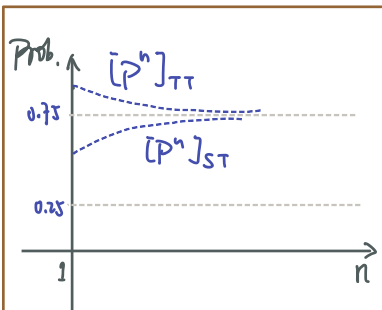


Fig 1

Remark 1. Suppose the limit exists and $\lim_{n \rightarrow \infty} \vec{\mu}(n) = \vec{\pi}$.

Then taking limits at both sides of

$$\vec{\mu}(n) = \vec{\mu}(n-1) \cdot P$$

yields $\vec{\pi} = \vec{\pi} P$.

That is, the limit is a left eigenvector of P with eigenvalue 1.

Def. (Stationary distribution)

A probability vector $\vec{\pi}$ (i.e., $\pi_i \geq 0, \forall i; \sum_i \pi_i = 1$)

is a stationary distribution of P if

$$\vec{\pi} P = \vec{\pi}.$$

Def. (Stationary measure)

A measure $\vec{\nu}$ on \mathcal{X} (i.e., $\vec{\nu} \in \mathbb{R}^{|\mathcal{X}|}$, s.t. $\nu_i \geq 0, \forall i;$

$\sum_i \nu_i > 0$) is a stationary measure of P if

$$\vec{\nu} P = \vec{\nu}.$$

Ex1 (cont.) Suppose the limit exists and $\lim_{n \rightarrow \infty} \vec{\mu}(n) = \vec{\pi}$.

Solving the system of equations with positivity constraints

$$\begin{cases} \vec{\pi} P = \vec{\pi}; \\ \pi_i \geq 0, i=1,2; \\ \pi_1 + \pi_2 = 1. \end{cases}$$

yields $\vec{\pi} = (0.75, 0.25)$ as the unique solution. Thus

$$\vec{\mu}(n) \xrightarrow{n \rightarrow \infty} (0.75, 0.25).$$

Here, $(0.75, 0.25)$ is the unique stationary distribution of P . For any $c > 0$, $c\vec{\pi} = (0.75c, 0.25c)$ is a stationary measure of P .

Ex2. SRW on \mathbb{Z}_4 .

$$P = \begin{array}{c|cccc} & [0] & [1] & [2] & [3] \\ \hline [0] & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ [1] & \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ [2] & 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ [3] & \frac{1}{2} & 0 & \frac{1}{2} & 0 \end{array} \quad \text{bi-stochastic}$$

Let $\vec{v} = (1, 1, 1, 1)$. Then $\vec{v} P = \vec{v}$.

Let $\vec{\pi} = c \vec{v}$ with $c = \frac{1}{4}$, then $\sum_i \pi_i = c \sum_i v_i = 1$.

Thus, $\vec{\pi} = (\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4})$ is a stationary distribution of P .

Remark 2. In general, if $|X| < \infty$, and \vec{v} is a stationary measure, then $\frac{\vec{v}}{\sum_i v_i}$ is a stationary distribution.

Ex3. SRW on \mathbb{Z} .

$$P = \begin{array}{c} \dots & -2 & -1 & 0 & 1 & 2 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ -2 & \dots & 0 & \frac{1}{2} & 0 & 0 & 0 & \dots \\ -1 & \dots & \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 & \dots \\ 0 & \dots & 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \dots \\ 1 & \dots & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} & \dots \\ 2 & \dots & 0 & 0 & 0 & \frac{1}{2} & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{array}$$

Let $\vec{v} = (\dots, 1, 1, 1, 1, 1, \dots)$, then

$$[\vec{v} P]_j = \sum_i v_i P_{ij} = \sum_i P_{ij} = \frac{1}{2} + \frac{1}{2} = v_j, \quad \forall j \in \mathbb{Z}.$$

This implies $\vec{v} P = \vec{v}$.

Notice that $\sum_i v_i = \infty$ and thus it cannot be normalized into a probability vector.

Q: Does P have a stationary distribution?

2° Proposition of Stationary distributions.

For $X_0 \sim \bar{\pi}$, then $X_t \sim \bar{\pi}$, for all $t \in \mathbb{N}$.

Key Questions:

Q1. When do stationary distributions exist?

Q2. Under Q1, when are they unique?

Q3. Under Q1 and Q2, suppose there exists

a unique stationary distribution $\bar{\pi}$, let

$\bar{\mu}(n)$ be the distribution of X_n under initial

data $X_0 \sim \bar{\mu}$, will it always be true that

$$\lim_{n \rightarrow \infty} \bar{\mu}(n) = \bar{\pi} \quad ?$$

3°. Detailed Balance condition:

Def. (Detailed Balance Condition)

$\vec{\pi}$ is said to satisfy the detailed balance condition

if

$$\vec{\pi}_x P_{xy} = \vec{\pi}_y P_{yx}, \quad \forall x, y \in \mathcal{X}.$$

Lemma 1: If $\vec{\pi}$ satisfies the detailed balance condition,

then $\vec{\pi}$ is stationary.

PF. For any $y \in \mathcal{X}$,

$$[\vec{\pi}P]_y = \sum_{x \in \mathcal{X}} \vec{\pi}_x P_{xy}$$

$$= \sum_{x \in \mathcal{X}} \vec{\pi}_y P_{yx}$$

$$= \vec{\pi}_y \sum_{x \in \mathcal{X}} P_{yx}$$

$$= \vec{\pi}_y \cdot 1$$

$$= \vec{\pi}_y.$$

Thus, $\vec{\pi}P = \vec{\pi}$.

Remark 3. (Interpretation of the detailed balance condition).

Given the initial data $X_0 \sim \vec{\pi}$, then $\forall x, y \in \mathcal{X}$,

$$\mathbb{P}(X_0 = x, X_1 = y)$$

$$= \mathbb{P}(X_1 = y \mid X_0 = x) \cdot \mathbb{P}(X_0 = x)$$

$$= P_{xy} \cdot \vec{\pi}_x$$

$$= P_{yx} \cdot \vec{\pi}_y$$

$$= \mathbb{P}(X_1 = x \mid X_0 = y) \cdot \mathbb{P}(X_0 = y)$$

$$= \mathbb{P}(X_0 = y, X_1 = x).$$

This is the end of this lecture !